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AUTOMATED SEGMENTATION OF BRAIN TUMORS IN MAGNETIC RESONANCE IMAGES USING ENHANCED ICA APPROACH

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ABSTRACT

The anatomical complexity of human brain makes the process of imaging and analyzing very difficult. In spite of huge advancements in medical imaging procedures, accurate segmentation and classification of brain abnormalities remains a challenging and daunting task. This challenge is more visible in the case of brain tumors because of different possible shapes of tumors, locations and image intensities of different types of tumors. In this paper we have presented a method for automated segmentation of brain tumors in images obtained from Magnetic Resonance Imaging (MRI). The method is based on Enhanced Independent component analysis (EICA) Mixture Mode Model. As a part of the research a Graphical user interface (GUI) is also presented. This GUI is capable of analyzing, segmenting and quantifying brain tumors. The results of the proposed method are validated by comparing it with different segmentation approaches like K-means, Fuzzy C-Means (FCM) and Watershed.

KEYWORDS: MRI, EICA, GUI, K-means, FCM and Watershed

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Original Article

INTRODUCTION

Technology has opened up new avenues in diagnosis and healthcare. Medical imaging is one such off shoot technological development that has been brought out for diagnosis and healthcare. Currently multiple imaging modalities are available to image specific organs or regions of the human body. Coupled with exponential growth in the processing power of computing system and the enhancement in the capacity of storage elements, the use of medical images has breached many boundaries. One of the important applications of medical imaging is analysis of the brain images. Very specifically computational neuro anatomy which includes automated analysis of neuro anatomical structures using different imaging procedures has become fore front of medical image processing [1]. One of the critical applications of neuro imaging procedures is identification and classification of brain tumors. This research work envisages a method for identification and classification of brain tumors. A Computer Aided Diagnosis (CAD) system that can serve as an effective tool for providing secondary clinical opinion is also developed as a part of this research work [2].

Human brain is considered as the most complex organ in the human body. Human brain is responsible for reception, processing, transmission, perception and interpretation of information. Brain along with spinal cord constitutes the central nervous system. Identification and classification of tumors is very crucial for planning treatment regime and can play huge role in determining the prognosis of the patient. There are different classifications of brain tumors. The primary classification is being primary brain tumors and secondary brain

tumors. Brain tumors can also be classified based on location of tumors, type of tissue involved and whether they are cancerous or noncancerous. The primary brain tumors are those tumors which originate in human brain and they can be either malignant or benign. Secondary tumors are those which originate from other parts of body and end up in human brain. They are at times referred as meta static brain tumors. Similarly the tumors can be graded depending upon the abnormality of cell appearance and the aggressive growth under the microscope.

Brain tumors being complex in view of its location and intricate structure of human brain are very difficult to diagnose and classify. Brain tumors remain one of the most common brain diseases that has affected and devastated many lives. According to data available with international agency for research on cancer (IARC), India ranks second for occurrence and mortality of brain cancers as of the year 2012 [3].

Anatomical segmentation of structures of human brain forms the preliminary step towards computer aided diagnosis and therapy [4]. Medical image segmentation being a complex and challenging task needs precise methods for identifying and segmenting different regions of interest. Especially in case of brain which has a specifically complex structure, its precise segmentation of structures is of at most importance. The literature presents a gamut of MRI segmentation approaches, most of the approaches fall under thresholding, region growing and clustering. In the case of brain image it is important to know that the distribution of tissue intensities is not uniform and it makes process of determining threshold very difficult. This factor makes the thresholding methods restricted and they have to be combined with other methods. One such extension is region growing where the thresholding is extended by combining it with connectivity conditions or regional homogeneity criteria.

Precise anatomical information is very much essential to identify single or multiseed pixels for each region along with their associated homogeneity. Of all the different types of methods available, clustering methods appear to be most popular and successful methods for medical image segmentation. These methods include FCM, K-means, Expectation maximization algorithms etc. In this research work, the objective is to segment the brain tumors using Enhanced Independent Component Analysis Mixture Model (EICAMM). The performance of the segmentation approaches is evaluated using different performance measures. They are Probabilistic Rand Index (PRI), Variation of Information (VOI) [5], Global Consistency Error (GCE) [6], Peak Signal to Noise Ratio (PSNR) [7], and Jaccard Distance (JD) [8]. As a part of this research work, a CAD tool is also presented in the form of a Graphical User Interface (GUI).

MRI FOR IMAGING OF BRAIN

There are numerous imaging modalities that can be used for studying brain tumors. These include magnetic resonance imaging (MRI), computerized tomography (CT), positron emission tomography (PET), single photon emission computed tomography (SPECT) and cerebral angiography. In spite of these different modalities, MRI remains the preferred method for visualizing the physiological or pathological changes of brain tissues [9].

MRI remains the preferred method for brain imaging owing to the fact that it is highly sensitive in detecting brain abnormalities during the early stage of disease. It also has excellent detection capabilities for brain tumors, cerebral infarction and other infections. In regard to brain magnetic resonance images T1 and T2 relaxation times play a very crucial role in determining signal intensity and contrast. There is a distinct differentiation of contrast on T1 and T2 weighted images. Similarly brain pathology also has some common signal characteristics. The type of pathology and its contrast in T1 and T2 weighted images [4] is illustrated in form of the table (1) below

Table 1: Pathology and its Contrast in T1 and T2 Weighted Image [4]

Pathology	Contrast in T1 Weighted Image	Contrast in T2 Weighted Image
Solid mass	Dark	Bright
Fat	Bright	Dark
Cyst	Dark	Bright
Acute and chronic blood	Gray	Dark
Sub acute blood	Bright	Bright

Some of the problems are common to both computed tomography and magnetic resonance medical images. These problems include partial volume effect, different kinds of artifacts like motion artifact, ring artifact etc., and noise due to sensors and related electronic systems. The typical artifacts that are present in magnetic resonance imaging systems include Partial volume, RF noise, Intensity homogeneity, Gradient, Motion, Wrap around, Gibbs ringing and Susceptibility

SEGMENTATION APPROACHES

The primary objective of image processing is to optimize the visualization and interpretation of a particular thematic data set. The applications and the end objectives typically define the image processing methods and strategy. The very first step towards identification and understanding the content conveyed by an image is to segment and identify the different objects in it. The process of segmentation renders an image in to different divisions/regions which have similar attributes.

One of the basic attribute for segmentation in the case of a monochrome image is its amplitude-luminance factor and in the case of colour image it is the colour components. Apart from this attribute other features like image edges and textures also play a very crucial role in segmentation. At the end of segmentation, a set of regions that collectively cover entire image or a set of contours is extracted from the image. It is important to understand that the process of segmentation does not essentially involve in classifying each segment. The basic process of segmentation tries to subdivide the image based on different attributes and it does not attempt to recognize the individual segments or correlate the relationships between the segments. Being the fundamental step in most of image processing applications, especially for machine learning and classification, image segmentation can be considered as a most crucial stage of data processing

A survey of literature reveals that the image segmentation techniques can be classified in to different types [10]. Typically the image segmentation approaches falls under any one of the following categories.

- Edge based segmentation
- Threshold based segmentation
- Region based segmentation
- Cluster based segmentation
- Hybrid based segmentation

In the case of edge based segmentation [11], the algorithms attempt to resolve the image by detecting the edges between different regions. These edges which are characterized by sudden changes in the intensity value are extracted and grouped to form closed region boundaries.

Threshold based segmentation [12] is one of the oldest and most powerful techniques employed for segmenting different types of images. The fundamental idea in this approach is to use the threshold to divide the pixels based on the intensity value. Those pixels which are having higher intensity values than the threshold are grouped in to a particular class and those pixels which are having intensity values less than threshold are grouped in to a different class.

The region based methods [11] attempt to segregate the images into different regions. These regions are categorized based on similarity or dissimilarity in regard to a set of predefined conditions.

Clustering [13] is very versatile segmentation approach in which the image is categorized in to different clusters. The clusters are formed by predefining certain similarity conditions between the pixels. Once these conditions are predefined, similar pixels are identified and grouped to form different clusters. Clustering does not alter the intensity values of the images and are hence primarily suited for analysis of medical images. This is very much essential because of the fact medical images contain valuable clinical information embedded in the form of different shapes, structures, morphology and intensity. It is very much essential that image processing approaches do not alter these attributes and there by skewing the clinical information content in them.

The hybrid approaches [14] combine any two of the above methods and are typically influenced by the application to which they are proposed to be employed. These hybrid methods tend to exploit the advantages of those two methods and compensating for their inherent limitation. In this research work apart from the proposed method of segmentation, three different segmentation methods are studied. These three methods include segmentation by K-means clustering [15], segmentation by Fuzzy C means clustering [16] and Watershed segmentation [17].

PROPOSED APPROACH

Independent Component Analysis (ICA) can be identified as technique for identifying linear non orthogonal coordinate systems in multivariate data [18]. The data's second and higher order statistics determine the direction of axis of this coordinate systems. The primary goal of ICA is to provide linear transformation of data so that the transformed variables are statistically independent from each other as far as possible. In other words, ICA generalizes the technique of principal components analysis (PCA) and like PCA [18], it is a very useful tool for finding structure in data. One limitation of ICA lies in its assumption that the sources are independent. In order to relax this assumption the concept of mixture models have been introduced. In the case of mixture model, the observed data is characterized into several mutually exclusive classes. In order to improve the generalization performance of ICA it is imperative to choose a proper search space. Very specifically for generalization considerations ICA should be preceded by dimensionality reduction procedures. Preceding ICA with a proper dimensionality reduction procedure like PCA will enhance the generalization performance of ICA and at the same time will reduce the computational complexity.

In this proposed work enhancement for the ICA is done at the following levels.

- Enhancement in regard to the energy criteria. The Eigen values determine the effectiveness of the features in terms of representing the original data and the Eigen value spectrum really indicates the energy of original data. It should be ensured when the transformations are effected from a high dimensional space to a lower dimensional space, it should be constrained in such a way that the representative information of original data is preserved as much as possible.
- Enhancement in regard to magnitude criteria. The implementation according to this criterion should be in a

reduced PCA space where the Eigen values do not include small valued trailing Eigen values. Thus according to this criterion which favors low dimension spaces, the small valued trailing Eigen values are excluded.

The proposed work is based on the concept that for enhanced performance the dimensionality reduction procedures should preserve a proper balance between energy criterion and magnitude criterion.

It is assumed that the images are preprocessed using PCA for enhancing the performance of subsequent ICA operations. The steps include

- Implementing the ICA.
- Extracting the independent components and negative independent components.
- Implementing entropy based thresholding
- Segmenting the suspicious tumor regions.

In order to further enhance the implementation of ICA by improving the convergence rate and reducing the complexity fast fixed point algorithm [19] is considered for implementation of ICA.

The observed signals are considered to be a linear combination of the original signals and a mixing matrix. It can be represented as

$$X = AS \tag{1}$$

To obtain the mixing matrix A, we compute its $W=A^{-1}$ inverse and obtain the IC as

$$\hat{S}=\mathrm{WX}, \tag{2}$$

$$\hat{S}=\mathrm{S}. \tag{3}$$

The objective here is to segment suspicious regions from an IC. For a start, we let t_{ij} be the $(i, j)^{th}$ element of a co-occurrence matrix W that considers the gray level transitions between two adjacent pixels. The equation is defined as

$$t_{ij=} \sum_{i=l}^{M} \sum_{k=1}^{N} \delta(l.k) \tag{4}$$

where

$$\delta_{d,\theta} = \begin{cases} 1, \\ 0, \end{cases} \text{if } I(l+1,k)=i,\ I=I(l,k)=i,\ I(l,K+1)=j \text{ and/or } I(l,k)=i,\ I(l+1,k)=j,\ \text{Otherwise} \tag{5}$$

The probability of a transition of this gray level from i to j can be defined as

$$\mathrm{p_{ij}} = \frac{\mathrm{t_{ij}}}{\sum_{\mathrm{i}=0}^{\mathrm{L}-1} \sum_{\mathrm{j}=0}^{\mathrm{L}-1} \mathrm{t_{ij}}} \tag{6}$$

If *'t'* is the threshold used to threshold an image Then, the t partitions the co-occurrence matrix as defined by Eq. (5) can be grouped into four quadrants, A, B, C, and D.

Further these quadrants can be grouped in to classes, with an assumption that the pixels with intensity levels above the threshold are assigned to the foreground objects and those below or equal is assigned to background objects.

Quadrants A and C represents local transitions within the background and foreground, respectively, while quadrants B and D represent the transitions across boundaries between the foreground and the background.

The probabilities associated with each of these quadrants can be given by

$$P_{A=}^{t} \sum_{i=0}^{t} \sum_{j=o}^{t} P_{ij} \quad P_{B=}^{t} \sum_{i=0}^{t} \sum_{j=t+1}^{L-1} P_{ij}$$

$$P_{C=}^{t} \sum_{i=t+1}^{L-1} \sum_{j=o}^{t} P_{ij} \quad P_{D=}^{t} \sum_{i=t+1}^{L-1} \sum_{j=t+1}^{L-1} P_{ij} \tag{7}$$

The probabilities in each quadrant can be further obtained by so-called cell probabilities:

$$P_{ij|A}^{t} = \frac{P_{ij}}{P_A^t} \; P_{ij|B}^{t} = \frac{P_{ij}}{P_B^t} \; P_{ij|C}^{t} = \frac{P_{ij}}{P_C^t} \; P_{ij|D}^{t} = \frac{P_{ij}}{P_D^t} \tag{8}$$

In this work we have employed local entropy based thresholding to segment the tumor. Since the quadrants A and C represents local transitions from background to background (BB) and objects to objects (FF), respectively, the local entropies can be defined as

$$H_{BB}(t) = -\sum_{i=0}^{t} \sum_{j=0}^{t} P_{ij|A}^{t} \log P_{ij|A}^{t} \tag{9}$$

$$H_{FF}(t) = -\sum_{i=t+1}^{L-1} \sum_{j=t+1}^{L-1} P_{ij|C}^{t} \log P_{ij|C}^{t} \tag{10}$$

By summing up the local within-class transition entropies of the foreground and the background, second-order local entropy can be obtained as

$$H_{LE}(t) = H_{BB}(t) + H_{FF}(t) \tag{11}$$

The above equation can be maximized to obtain a threshold based on local entropy and the tumor can be segmented.

$$t_{LE} = \arg\{_{t}^{max} H_{LE}(t) \tag{12}$$

COMPUTER AIDED DIAGNOSIS (CAD) TOOL

With the increased volume of images, computer aided diagnosis can be of great help in identification of diseased condition and in the management of particular disease. The necessity for computer aided diagnosis especially in the case of brain image analysis is very huge. Manual and visual interpretation of images can lead to subjective assessment which is prone to human errors. Apart from this fact there is also a necessity to provide a quality secondary opinion for a radiologist or a clinical practioner to concur with. Detection and quantification are integral to any diagnosis and the help of computer in this aspect will go a long way in healthcare management. It is with this objective a CAD tool has been designed for automatic segmentation and classification of brain tumor in magnetic resonance images.

A comprehensive tool capable of performing segmentation and different analysis as required by the user is designed. The tool is proposed to be in the form of a Graphical User Interface (GUI) which enables the user to have ease of operation in loading the image, segmenting it and analyzing it. The tool is coded using Matlab Version 14. A Graphical User Interface enables the user to have seamless use and flexibility of operation. The implementation is carried out in a system having Core 2 Duo processor cloaking at a speed of 2 GHz with a RAM of 2GB. The screen shot of the tool is given in the figure.

The tool as such can be demarcated in to 7 different functional regions. Each region has specific functional and analysis elements inbuilt in to them.

Region 1: This is the Input / Output region of the tool. The tool is capable of handling images in normal image

formats like,.jpg,.bmp,.tiff and also it is capable of handling DICOM images. Using the tool a series of DICOM images can also be fed as input for 3D Visualization. In the output section, function elements here enable to save the image in current display window for further analysis. The output section also has the capability to save 3D volume information in the case of series images being read.

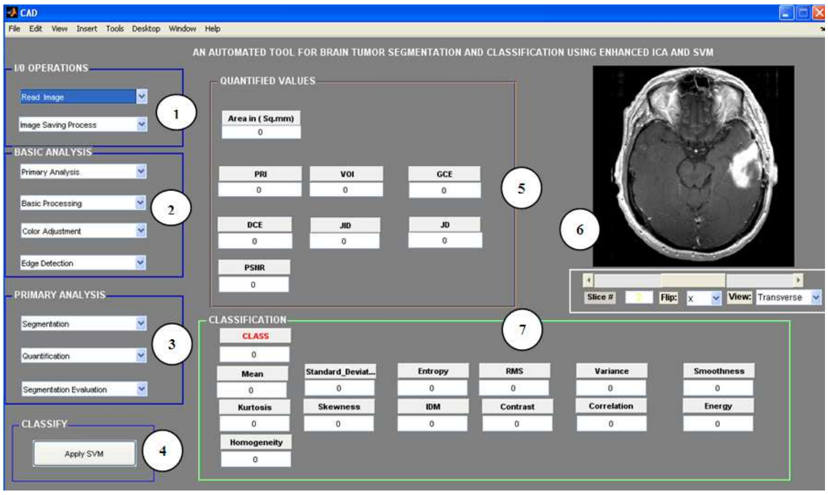

Figure 1: The Screen Shot of the CAD Tool

Region 2: **T**his section helps the user in performing basic analysis of the images; the image can be either the MRI image of the whole brain or the segmented image as obtained by the tool. This section has 4 sub functional sections like;

Initial Analysis: This includes, Histogram Analysis, Pixel Profile of a particular region of the image and a specific tool for adjusting the image intensity for better visualization.

Basic Processing: This incorporates analysis like, Image adjusts for smoothening, histogram equalization, and wiener smoothening and morphology based analysis.

Color Adjustment: This has the option of viewing the image in different color spaces like, hot, gray and jet. This helps in better visualization of images.

Edge Detection: Different edge detection operations like, Prewitt, Sobel, Canny, Log, Roberts and Zero crossing operators are implemented for edge analysis.

Region 3**:** This is the primary analysis section in which the segmentation, quantification and evaluation of segmentation is carried out.

Segmentation: K means segmentation, Watershed segmentation; Fuzzy c means segmentation and Enhanced ICA Mixture model based segmentation are implemented here.

Quantification: The area of the segmented Brain tumor is calculated using this functional icon.

Segmentation Evaluation: The performance of the segmentation approaches is evaluated using different performance measures they are Probabilistic Rand Index (PRI), Variation of Information (VOI), Global Consistency Error (GCE), Peak Signal to Noise Ratio (PSNR), Dice coefficient (DCE) and Jaccard Distance (JD).

Region 4: The classification of the tumor as possibly 'Malignant/ Benign' is carried with the help of the functional icon. This initiates the process of SVM classification. The segmented image which is displayed in the current

axis is considered as the input for the SVM classifier. The image features are extracted using DWT, reduced using PCA and subsequently classified with the help of Kernel SVM. During each classification the SVM is trained using a preloaded data set.

***Region 5*:** This visual representation of the different analysis and processing is displayed here. It has the capability to handle both 2D and 3D images.

***Region 6*:** The quantified results are presented here. This includes the value for the estimated tumor area and the value for different parameters used for evaluation segmentation.

***Region 7*:** This region displays the features that are extracted from the segmented image.

RESULTS AND DISCUSSIONS

In order to illustrate the different segmentation approaches implemented in this tool and other aspects of the tool the following image is considered as a test image. The image slice and its corresponding histogram are given in the figure (2) below.

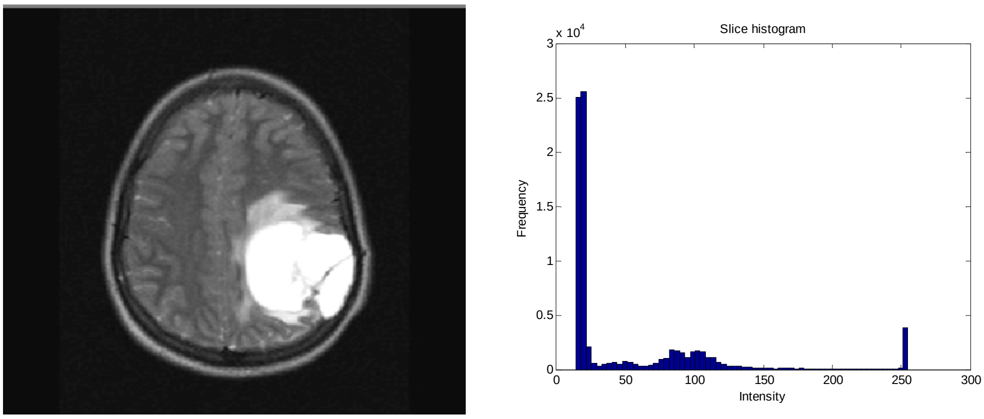

Figure 2: Input Brain MRI and its Histogram

The figure (3) presents the results of segemnation of three different approaches like K means segmentation, Watershed segmentation; Fuzzy c means segmentation. Image processing is a subjective analysis and more so in the case of medical image processing, it can be observed from the figure, K means based clustering provides a better segmentation of the image when compared to the other two approaches for this particular image. Even though watershed segmentation clearly demarcates regions, the design of this tool is such that the segmented results are used for quantifciaton of the area of the tumor.

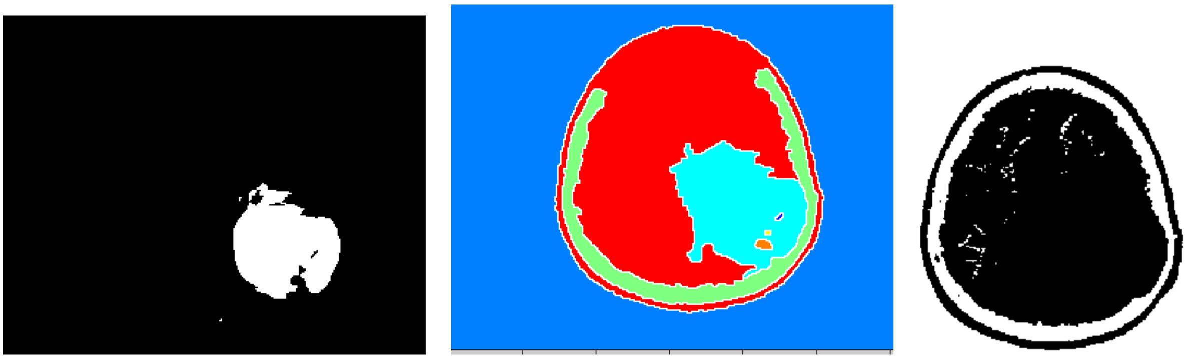

Figure 3: Segmentation Results of K Means, Watershed and FCM Methods

The results of the segmentation using the proposed approach is illustrated in the following figure (4); a visual interpretation of the image reveals a clean segmentation.

Figure 4: Segmentation Result for the Proposed Method

To compare the intensity profile of the original image and the segmented tumor, a histogram analysis is implemented.

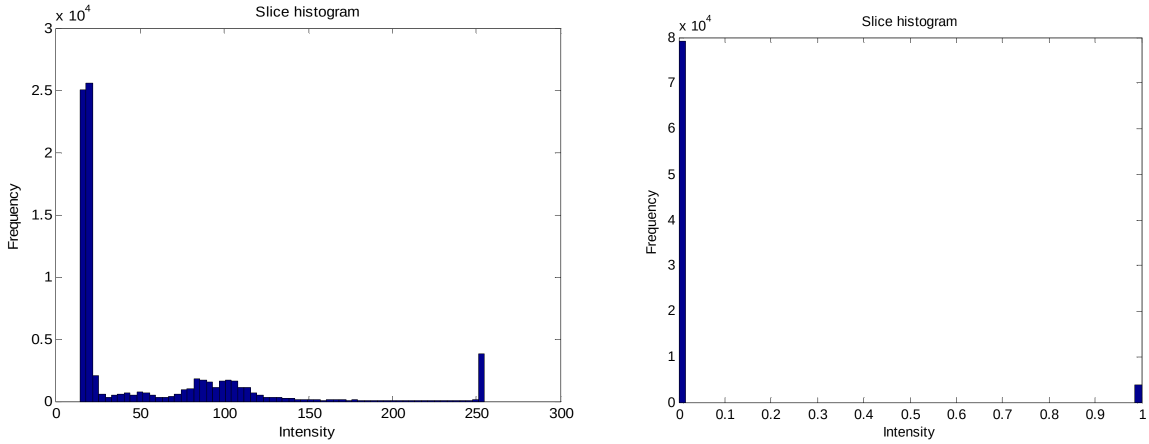

Figure 5: Histogram of the Original Image and Histogram of the Tumor Segmented using the Proposed Approach

The histogram analysis of the image reveals the distribution of pixels in images pre and post the segmentation. It can be clearly observed from the figure (5) there is narrowing of distribution of the pixel intensities in regard for the segmented tumor. It can be clearly observed that; the tumor is segmented very clearly and neatly distinguished. This will also help a long way in effective quantization of the tumors. This fact is also emphasized by comparing the histograms of the original image and of the segmented tumor.

The histogram of the original image show the presence of multiple intensity components, where as the histogram of the segmented image clearly shows the level of segmentation as only few components pertaining to the tumor are present. This shows the effectiveness of segmentation and negligible presence of other intensity components pertaining to background or other structures in the original image. Similarly intensity profile analysis of the original image in column presumably containing the tumor and of the corresponding analysis in segmented image also strengthens these facts. This is illustrated in the Figure (6).

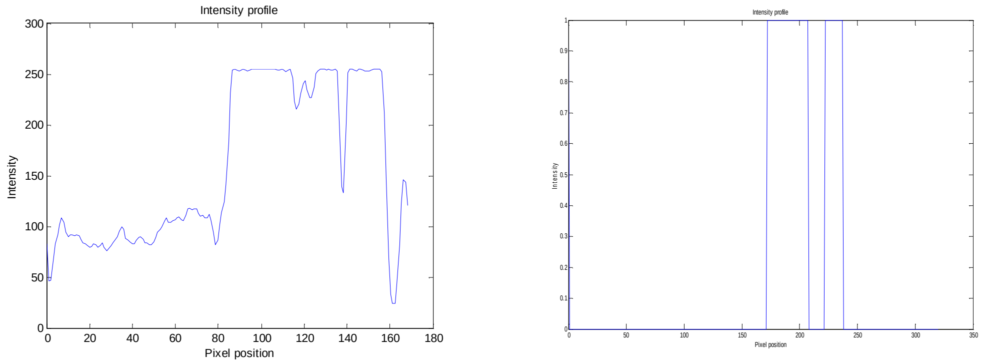

Figure 6: Intensity Profile of a Row in the Original Image and Intensity Profile of the Same Row in the Segmented Image

The visual interpretation of the segmented image illustrates better performance of the proposed approach in comparison to the other segmentation approaches. The results of the segmentation are also quantified by comparing the segmented results against a ground truth. The ground truth image is obtained through manual segmentation with the help of a radiologist. The performance of different algorithms when quantified using different parameters is illustrated using Table 2.

Table 2: Segmentation Evaluation Parameters for different Segmentation Approaches

Method	PRI	VOI	GCE	PSNR	JD
K-Means	0.8923	0.3620	0.165	32.274	0.54145
FCM	0.653922	1.03529	0.06886	2.88232	1
Watershed	0.920574	0.249161	0	16.6498	0.850062
Proposed Approach	0.994645	0.0411189	0.00496949	63.2818	0.0483871

The table clearly points to the improved performance of the proposed method in the terms of different evaluation parameters. It can be clearly observed that the proposed method performance is appreciable in terms of PSNR. The overlap image illustrated in the figure (7) depicts a clean segmentation and perfect synchronization with the ground truth image.

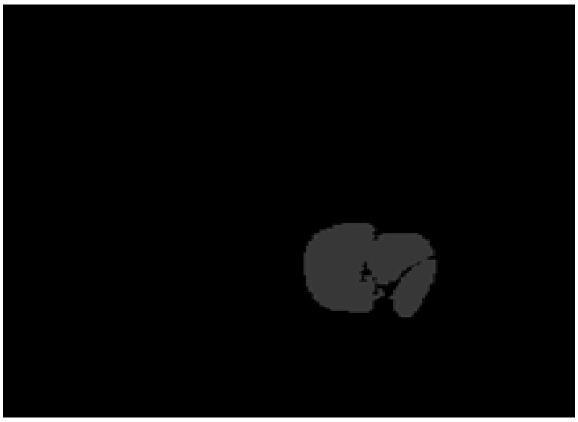

Figure 7: Overlap Image of Ground Truth and the Segmented Image

CONCLUSIONS

The utility of any image is implied by the quantum and quality of information that can extracted out of it. Humans have tremendous processing power and a very complex way on interpreting and making a cognitive analysis of an image. The typical issues with visual interpretation include, wide difference in sense of perception between different users, human

fatigue and most of the time it will be a qualitative analysis rather than a quantifiable one. In this work we have successfully presented a method of image segmentation which can help in the automatic segmentation of brain tumors in MRI. Through visual interpretation and by comparing the different evaluation parameters it can be safely concluded that the proposed approach has better performance in comparison with other methods illustrated in this research work. The improvement in performance is significantly visible in all parameters.

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